Optimizing Remote Sensing and GIS Tools for Mapping and Managing the Distribution of an Invasive Mangrove (Rhizophora ....

Article in Marine Geodesy · May 2007
DOI: 10.1080/01490410701296663

CITATIONS
13

READS
124

4 authors, including:

Stacy Jupiter
Wildlife Conservation Society

Donald Cameron Potts
University of California, Santa Cruz

Some of the authors of this publication are also working on these related projects:

Locally Managed Marine Areas Network View project

Brine Discharge From Desalination Plants – Impacts on Coastal Ecology and Coastal Communities View project

All content following this page was uploaded by Susan A. Cochran on 20 October 2015.

The user has requested enhancement of the downloaded file.
Optimizing Remote Sensing and GIS Tools for Mapping and Managing the Distribution of an Invasive Mangrove (Rhizophora mangle) on South Molokai, Hawaii

Mimi D'iorio, Stacy D. Jupiter, Susan A. Cochran & Donald C. Potts

To cite this article: Mimi D'iorio, Stacy D. Jupiter, Susan A. Cochran & Donald C. Potts (2007) Optimizing Remote Sensing and GIS Tools for Mapping and Managing the Distribution of an Invasive Mangrove (Rhizophora mangle) on South Molokai, Hawaii, Marine Geodesy, 30:1-2, 125-144, DOI: 10.1080/01490410701296663

To link to this article: http://dx.doi.org/10.1080/01490410701296663

Published online: 15 May 2007.

Submit your article to this journal

Article views: 211

View related articles

Citing articles: 5 View citing articles
Optimizing Remote Sensing and GIS Tools for Mapping and Managing the Distribution of an Invasive Mangrove (*Rhizophora mangle*) on South Molokai, Hawaii

MIMI D’IORIO,1 STACY D. JUPITER,2 SUSAN A. COCHRAN,3 AND DONALD C. POTTS2

1Department of Earth Science, University of California, Santa Cruz, California, USA
2Ecology and Evolutionary Biology Department, University of California, Santa Cruz, California, USA
3United States Geological Survey, Pacific Science Center, Santa Cruz, Hawaii

In 1902, the Florida red mangrove, *Rhizophora mangle* L., was introduced to the island of Molokai, Hawaii, and has since colonized nearly 25% of the south coast shoreline. By classifying three kinds of remote sensing imagery, we compared abilities to detect invasive mangrove distributions and to discriminate mangroves from surrounding terrestrial vegetation. Using three analytical techniques, we compared mangrove mapping accuracy for various sensor-technique combinations. ANOVA of accuracy assessments demonstrated significant differences among techniques, but no significant differences among the three sensors. We summarize advantages and disadvantages of each sensor and technique for mapping mangrove distributions in tropical coastal environments.

Keywords AVIRIS, ASTER, aerial photography, habitat mapping, classification accuracy, alien species management, red mangrove

Introduction

Mangrove habitats are ecologically and geologically valuable coastal resources that harbor a great diversity of organisms, filter dissolved and particulate materials crossing the land-sea interface, and stabilize and protect eroding coastlines (Lugo and Snedaker 1974). Because the condition of a mangrove ecosystem is intimately linked to the interaction of marine, terrestrial, and meteorological factors, mangrove systems respond rapidly to changing terrestrial, oceanographic, and climatic conditions over short time scales. Because they are restricted to higher intertidal levels, mangroves are one of the first systems to experience sea-level rise and are potentially sensitive indicators of coastal change induced by both natural and anthropogenic forces (Blasco et al. 1996; Ellison and Farnsworth 1997; Alongi 2002). While mangrove forests can be seriously damaged by severe storms (Imbert et al. 1996; Sherman et al. 2001), they also buffer inland areas against strong storm surges.
For example, coastal areas fringed by mangroves during the 2005 Asian tsunami were less damaged than cleared regions (Danielsen et al. 2006). Therefore, the ability to map mangrove ecosystems, evaluate their structure and condition, and detect changes rapidly and affordably is important for assessing regional to global environmental change.

Worldwide, most natural mangrove systems are declining from overharvesting, land reclamation, and aquaculture (Spalding et al. 1997; Alongi 2002), leading to large-scale efforts in many countries to restore degraded mangroves and preserve remaining natural mangrove systems. Hawaii, which lacked mangroves before European contact, provides an unusual contrast because the success and rapid proliferation of introduced mangroves over the last century has created other environmental concerns: habitat loss of four endangered waterbirds, destruction of historic fishponds, and restructuring of the coastal wetland ecosystem (Allen 1998; Cox and Allen 1999). These impacts on native systems have encouraged local agencies to develop and implement alien species management strategies for mangroves.

Although the Hawaiian Islands are suitable climatic and geomorphic settings for mangroves and propagules of some genera (e.g., Rhizophora) remain viable for several months (Duke et al. 1998), biogeographic barriers to dispersal via the northern Pacific gyre prevented natural colonization prior to human introduction (Ricklefs and Latham 1993). In 1902, the American Sugar Company deliberately imported the Florida red mangrove, Rhizophora mangle L., to Molokai to stabilize mudflats and protect the shorelines and nearshore reef environments from increased agricultural runoff associated with the cultivation of the uplands for sugar cane (MacCaughy 1917). Moberley (1968) hypothesized that the later establishment of R. mangle in Kaneohe Bay, Oahu, over 50 km to the northwest, was the result of surface transport of pods driven by trade winds from Molokai to the adjacent island. R. mangle has now been positively identified on at least six of the eight main Hawaiian Islands (Allen 1998).

The introduction of R. mangle substantially altered the dynamics and morphology of Molokai’s southern coastal zone over the last century. Since 1902, R. mangle has spread eastward along the Molokai coastline, leading to seaward progradation of the shoreline up to 400 m across the reef flat, filling of culturally important ancient fishponds and encroachment onto private beachfronts (Wester 1981; D’Iorio 2003). Historical rates of mangrove progradation (1915–2000) reflect increased sedimentation resulting from changing land use practices and are also correlated with watershed slope, coastal watershed area, and average reef width (D’Iorio 2003). Mangroves may have improved water quality along some coastal reef flats by trapping terrigenous materials (Bigelow et al. 1989), but they have also impeded drainage from narrow channels in urbanized areas, requiring costly removal (Wester 1981; Allen 1998; Chimner et al. 2006).

Other ecological consequences of mangrove introduction forecast by Egler (1947) have been equally dramatic. Contrary to early invasion theory which suggests that islands are more susceptible to introductions because their biota are fragile and less competitive (Elton 1958), Simberloff (1995) proposed that the success of R. mangle in Hawaii is due to the absence of native intertidal forest communities, rather than to superior competitive abilities. The proliferation of R. mangle is hindering population recovery of four endangered waterbirds—the Hawaiian stilt (Himantopus mexicanus knudsenii), Hawaiian duck (Anas wyvilliana), Hawaiian coot (Fulica alai), and Hawaiian moorhen (Gallinula chloropus sandvicensis). Mangrove detritus, toxic to many detritivores, also may affect detrital food webs in the sediment and pore waters (Alongi and Sasekumar 1992; Smith et al. 2000). At the same time, the mangroves may be facilitating increases in some native and introduced intertidal species by creating complex habitats within the network of prop roots and increasing available energy supplies from accumulating leaf litter (Simberloff 1995).
Remote sensing from spaceborne and airborne platforms has great potential for rapid assessment of rates of mangrove ecosystem change and for exploring impacts of introductions of alien mangrove species on natural systems, but all currently available remote sensing platforms require tradeoffs between cost, analysis time, level of discrimination and accuracy. Despite extensive, labor-intensive post-processing demands and the lack of global coverage (Lucas et al. 2002), aerial photography is still widely used for mapping coastal environments, including mangrove systems (Saintilan and Wilton 2001; Battiau-Queney et al. 2003; Higinbotham et al. 2004; Dahdouh-Guebas et al. 2004; Jupiter et al. 2006), but a growing body of work is using spaceborne remote sensing to investigate mangrove ecosystems worldwide. Multispectral satellite-based instruments have been used to define mangrove areas and assess baseline ecosystem conditions in many places (Bina et al. 1978; Lorenzo et al. 1979; Dutrieux et al. 1990; Jensen et al. 1991; Eong et al. 1992; Ramsey and Jensen 1996; Gao 1998; Ramirez-Garcia et al. 1998; Blasco and Aizpuru 2002; Haito et al. 2003; Jupiter et al. 2006), but analyses are often limited by low spectral and spatial resolutions of the sensors (Green et al. 1998). Such problems may be overcome by the increased spectral resolution of hyperspectral sensors, such as the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), which offer many advantages for detailed wetland community mapping. For example, Hirano et al. (2003) used AVIRIS to identify mangrove plants to species level and to successfully map the invasive lather leaf (Colubrina asiatica) in the Florida everglades. Yet widespread use of hyperspectral technology is still limited by high acquisition costs, exceptionally large data files, long processing times, and difficulties in co-registering repeated overflights (Smith et al. 1998; Hirano et al. 2003).

We used the reef- and mangrove-fringed southern coastline of Molokai as a case study to compare three kinds of remote sensing imagery, differing in spectral and spatial resolutions, and three analytical approaches for mapping invasive mangrove distributions. The image types were color aerial photography, multispectral satellite Advanced Spaceborne Thermal Emissions and Reflectance Radiometer (ASTER), and airborne hyperspectral AVIRIS data. We analyzed each three ways to evaluate the ability to discriminate mangrove from nonmangrove habitat. By integrating in situ field data within a geographical information system (GIS), we assessed the accuracy of each combination of imaging sensor and analytical approach and determined which provides the most effective and accurate classifications.

This study had three goals:

1. To validate the use of three widely used remote sensing technologies, integrated with field data and accuracy assessment, as a tool for mapping mangrove cover and tracking ecosystem responses to invasive species.
2. to assess the accuracy of three standard processing techniques used to analyze and classify remote sensing data of varying spatial and spectral resolutions, and
3. to discuss the application of GIS and remote sensing for coastal management in Hawaii.

Materials and Methods

Study Area

Molokai (21°N, 157°W) is the fifth largest island in the Hawaiian chain, covering about 676 square kilometers and rising 1515 m above sea level (Figure 1). The south coast has
the largest living fringing reef in the Hawaiian Islands, a nearly continuous, 2 km wide, carbonate structure that extends for roughly 50 km.

We concentrated on a 6 km² area in the coastal Pala’au region where *Rhizophora mangle* saplings were originally planted in 1902 (Allen 1998) (Figure 1). In this region, rainfall averages 70 cm yr⁻¹, falling mainly in the winter during brief, severe Kona storms that cause sheet wash and gullying. Climate changes, variations in land-use practices, and overgrazing of uplands by feral and domestic animals have led to vegetation loss, accelerated erosion, and extensive coastal sedimentation (Allen 1998). The coastal plain landward of the mangrove fringe is an extensive mud flat composed predominantly of fine-grained, lateritic mud and clay. This mud flat is hypersaline and rarely inundated by tides. It is occupied by dense *Batis maritima* (pickleweed) populations, sparse *Pluchea*
Table 1
Sensor Specifications for Aerial Camera (1:10000 scale); ASTER (Advanced Spaceborne Thermal Emissions and Reflection Radiometer) and, AVIRIS (Advanced Visible/Infrared Imaging Spectrometer); VNIR = Visible—Near Infrared; SWIR = Short Wave Infrared; TIR = Thermal Infrared

<table>
<thead>
<tr>
<th>Aerial Camera*</th>
<th>ASTER</th>
<th>AVIRIS**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Platform</td>
<td>Airborne</td>
<td>Spaceborne</td>
</tr>
<tr>
<td>Swath Width</td>
<td>Variable</td>
<td>60 km</td>
</tr>
<tr>
<td>Spatial Resolution</td>
<td>Variable</td>
<td>VNIR: 15 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SWIR: 30 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TIR: 90 m</td>
</tr>
<tr>
<td>Spectral Range</td>
<td>400–700 nm</td>
<td>520–12000 nm</td>
</tr>
<tr>
<td>Number of Bands</td>
<td>1</td>
<td>VNIR: 4 bands</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SWIR: 5 bands</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TIR: 5 bands</td>
</tr>
<tr>
<td>Band Width</td>
<td>300 nm</td>
<td>60–700 nm</td>
</tr>
</tbody>
</table>

*Non-digital, using film emulsion technology.
**High altitude AVIRIS flown at 20 km.

indica (Indian fleabane) patches, salty mud flats, and infrequent groves of Prosopis pallida (kiawe) (Figure 1).

Remote Sensing Data Sources
All images used in this study were acquired during 2000, with specifications for each data type listed in Table 1.

Aerial photography. Color aerial photographs were collected for the U.S. Geological Survey by Air Survey Hawaii in April 2000 at a scale of 1:10,000. We scanned the image diapositives at 1200 dpi using a high-resolution photogrammetric scanner to preserve high spatial resolution (0.25 m) and to maintain geometric relationships during digital conversion. Digital stereo images (overlapping 60%) were orthorectified using surveyed ground control points (±10 cm) and then mosaicked into a rectified orthophotomosaic covering approximately 20 km² of the south coast of Molokai. The root mean squared error (RMSE) values for the rectification, coupled with the ground resolution and ground control accuracy, provide an average error of ±0.5 m horizontally and ±1.0 m vertically for placement of every image pixel. The rectified orthophotomosaic served as the grid template for construction of a reference point matrix for accuracy assessment. The digital orthophotomosaic was resampled to 1 m and to 20 m (using nearest neighbor transformation) for comparing results from varying spatial resolutions.

ASTER multi-spectral imagery. ASTER images were collected by NASA’s Earth Observation Systems’ Terra satellite in November 2000. The data were acquired as ASTER Level 1B Calibrated Radiance at the Sensor, and delivered as radiometrically calibrated and geometrically corrected radiances (Wm⁻² sr⁻¹µm⁻²) that had been processed to remove effects of rotation of the earth and the variable position of the spacecraft. The radiance values were converted to apparent surface reflectance using the atmospheric correction algorithm, ACORN v. 3.12 (Analytical Imaging and Geophysics 2001), which applies Modtran 4
radiative transfer modeling to quantify and remove influences of aerosol scattering and atmospheric gases. Because ASTER spatial resolution varies with the spectral region, the VNIR bands were resampled from 15 to 30 m before combining with the SWIR bands for processing.

**AVIRIS hyperspectral imagery.** AVIRIS hyperspectral imagery was collected by NASA in April 2000 from a modified ER-2 aircraft flying at approximately 20,000 m, yielding $17 \times 17$ m ground pixels along a $\sim 10.5$ km wide swath flown from east to west along the south coast. The AVIRIS data were converted to apparent reflectance using the ATREM atmospheric correction (ATmospheric REMoval Program) (Gao et al. 1993). ATREM uses an atmospheric scattering model adapted from MODTRAN 5S radiative transfer code to convert raw radiance values at the sensor to actual surface reflectance.

**Pre-Processing**

Since the inland limit of the Pala’au mangrove forest was not completely encompassed by the ASTER imagery and clouds covered approximately 15% of the region, all datasets were spatially subset to the same 6 km$^2$ region of Pala’au that was visible in the nonclouded parts of the ASTER image. Because ATREM correction applied to AVIRIS data tends to overcompensate in water absorption regions of the spectrum, wavebands in these regions (0.94, 1.13, 1.37, 1.9 $\mu$m) were masked out. Wavebands at CO$_2$ absorption features (1.6 and 2.0 $\mu$m) were also masked out. All clouds and marine and near-shore reef environments were masked from all datasets by applying band thresholding techniques to a Minimum Noise Fraction transformation (MNF). The MNF transformation is a two-step process that decorrelates noise from the data, rescales the data with unit variance in every band, and is followed by a standard principle components analysis (Lee et al. 1990; Hirano et al. 2003). Band thresholding of primary MNF bands can help identify similar materials, which can be excluded or masked from subsequent analyses.

**Classification Techniques**

We processed all three datasets with ENVI version 3.5 (Research Systems Inc., Boulder, CO., USA) and PCI Geomatics’ APEX photogrammetric software (for orthorectification of aerial photographs). The following image analysis approaches were then applied to each image: (I) visual interpretation; (II) ISODATA unsupervised classification; and (III) Spectral Angle Mapping supervised classification. Each technique was applied to the same Pala’au region subset from color aerial photographs, combined VNIR-SWIR ASTER imagery, and the AVIRIS imagery. The accuracy of each mangrove classification was quantified individually with a contingency-based error matrix calculated between classified pixels and reference data.

**(I) Visual interpretation.** The images were enhanced to heighten tonal contrasts and facilitate mangrove canopy discrimination using an equalization stretch combined with a $3 \times 3$ median filter. Mangrove habitats were delineated by manually digitizing the outer edge of the canopy based on visual contrasts and referenced field data. To assess observer biases, the images were visually interpreted independently by two individuals: one familiar with the site (I) and one who had not been to the site (*I*).  

**(II) Unsupervised classification.** An Iterative Self-Organizing Data Analysis Technique (ISODATA) unsupervised classification was performed on each dataset. This iterative clustering routine is based on minimum spectral distances between each pixel and a
candidate cluster (ERDAS 1999). For all classifications, we specified 100 iterations, a convergence threshold of 99%, 25 maximum classes, and a minimum of 10 pixels per class. Mangrove classes were distinguished based on mean spectral reflectance curves and spectral features from field validation sites.

(III) Supervised classification. Using field data to guide the selection of homogeneous mangrove regions on each dataset, we applied ENVI’s Spectral Angle Mapper (SAM) supervised classification, which treats each spectrum as a multi-directional vector and calculates the n-dimensional angle between training spectra and the image spectrum of each pixel (see Fig. 9 in Hirano et al. 2003). We delineated regions of interest (ROIs) in known zones of mangroves and then used their mean spectra as input training classes to drive the SAM. Low SAM values reflect small spectral angles between training and image spectra, indicating high spectral correlation to the training endmember.

Georectification

After processing, all data were resampled to 5 m pixel sizes using the nearest neighbor method and geocorrected to the aerial orthophotomosaic with a second-order polynomial warping transformation. Fifty points were selected from the base orthophotomosaic and tied to points on the warp images. The RMSE values for registration of the ASTER and AVIRIS images were 1.8 pixels (9 m) and 1.3 pixels (6.5 m), respectively.

Accuracy Assessment

Green and Mumby (2000) recommended gathering field data from at least 50 sites per habitat class for a rigorous accuracy assessment of multispectral classifications, although data from high-resolution aerial photos may be substituted if access is difficult. Because of limited access to mangrove canopies, we were only able to collect 42 field validation points within the mangrove forests and along the fringes. At each location, an area of 20 m² was scored for dominant ground cover type: mangrove, nonmangrove, or mixed. We then viewed the aerial photographs in stereo to select an additional 165 points (for a total of 207) in the mangrove class. The nonmangrove reference class consisted of 150 points collected in the field, using a handheld GPS (<20 m positional accuracy) to record all locations. Points were predetermined by stratified random sampling of preliminary unsupervised classifications (Congalton 1991; Mumby et al. 1999).

The annotated GPS data and points selected from stereo aerial photographs collected during repeat field surveys were used to generate a reference grid of mangrove and nonmangrove points. Each classification was compared to the reference grid using a contingency matrix to calculate error statistics. A normalized 2 × 2 error matrix was calculated for each processing technique for each sensor to estimate the mangrove mapping accuracy of each combination (Congalton 1991). For this purpose, classes were grouped into “mangrove” and “nonmangrove.” The overall accuracy (the number of incorrect observations divided by the number of correct observations) is reported for each technique, and is partitioned into producer and user accuracy, each of which is reported with 95% confidence interval ranges calculated using the modified Wald method (Agresti and Coull 1998). Producer accuracy is the probability that the data processor has correctly classified pixels within a given reference class. It details errors of omission that result when a pixel is incorrectly classified into another category. User accuracy is the probability that a map user will correctly locate the class in the field based upon its identification on the map.
This statistic reflects errors of commission which result when a pixel is committed to an incorrect class. Tau coefficients indicate how many more pixels were correctly classified than expected by chance (Ma and Redmond 1995) and are used to assist consideration of accuracy by providing a readily interpretable coefficient with an approximately normal distribution that can be used in statistical comparisons. Tau values were arcsine square root transformed and analyzed in a two-way Model I ANOVA without replication to assess relative contributions to overall variance from sensor and classification technique. To determine differences in significance between techniques, we analyzed the transformed Tau values in a one-way Model I ANOVA and examined multiple comparisons using Tukey’s post-hoc test.

Results

Analyses of the same mangrove area, derived from three kinds of imagery, are summarized in Figure 2. Tau coefficients varied among sensors and analytic techniques, with a two-way ANOVA indicating that analytical processing technique contributed significantly to the variance in Tau coefficients ($P < 0.01$) and accounted for 69% of the overall variation (Figure 3, Table 2a). Sensor type explained only 13% of the overall variation and did
Figure 3. Mean tau coefficients for processing techniques: (I) visual interpretation with site familiarity; (I') visual interpretation without site familiarity; (II) unsupervised ISODATA classification; and (III) supervised SAM classification. Techniques (I, I') labeled a are significantly different from technique (III) labeled b. Error bars are standard error for each technique.

not contribute significantly to the overall variance (Table 2a). Tau coefficients showed significant differences between visual interpretation (I and I') and supervised classification techniques (III), while no significant differences existed between unsupervised ISODATA (II) and any of the other analytical techniques (Figure 3, Table 2b). Across all sensors, the visual interpretation technique had the highest mean overall accuracy, followed by ISODATA unsupervised classifications and SAM classifications (Table 3).

Table 2a
Summary of a two-way Model I ANOVA conducted on the Tau coefficients (Figure 3) for the overall accuracies of mangrove classification

<table>
<thead>
<tr>
<th>Source of variation</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>Fs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor</td>
<td>3</td>
<td>260.6</td>
<td>86.9</td>
<td>2.29 NS</td>
</tr>
<tr>
<td>Technique</td>
<td>3</td>
<td>1328.2</td>
<td>442.7</td>
<td>11.65**</td>
</tr>
<tr>
<td>Error</td>
<td>9</td>
<td>342.1</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>15</td>
<td>1930.9</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NS = not significant, ** = P < .01.
(I) Visual Interpretation

The visual interpretation technique consistently had higher overall accuracies than the other techniques for all three kinds of imagery (Table 3). The highest Tau values were for visual interpretation of color aerial photography using both the 1 m and 20 m datasets; accuracies were not significantly different when mangrove areas were delineated by individuals familiar (I) and unfamiliar (I∗) with the fieldsite (Figure 3, Table 2b). The overall accuracy of visual classifications ranged from 83.3% to 98.0%. Producer accuracies for all sensors were lower than user accuracies due to conservative digitizing of mangroves at ecotone borders.

(II) ISODATA

The unsupervised ISODATA classifications consistently had intermediate accuracies, lower than the visual ones but always more accurate than the supervised SAM classifications. ISODATA overall accuracies ranged from 79.6% to 89.6% (Table 3). The ISODATA algorithm failed to include all morphological varieties of *R. mangle* within the ASTER and AVIRIS classifications (errors of omission) and consistently excluded regions containing dwarf mangroves along the landward fringe, leading to lower producer accuracies (67.5–85.5%). User accuracies (95.3–96.3%) were also slightly lower for ISODATA classifications, probably because of misclassification of some upland pixels as mangroves (errors of commission) (Table 3).

(III) Spectral Angle Mapping

Because the training end member spectra used to generate the SAM classifications were averages of image-derived spectral signatures from known pure mangrove stands, the supervised SAM classifications were generally more conservation than other techniques, and also had the lowest average overall accuracies (65.5–72.2%) (Table 3). Mean Tau values for SAM classifications were significantly lower than for visual interpretation techniques (I and I∗) (Table 2b). Errors of omission reduced the producer accuracies for the mangrove class across sensor types to 44.4–52.2% (Table 3). The final SAM classifications did not contain the full morphological array or all geographic locations of mangroves within the zone and were heavily biased towards regions where the training class spectra were selected (i.e., dense mangrove cover). User accuracies of SAM classifications were lowest for aerial photographs, which had the greatest number of upland pixels misclassified as mangroves.

---

**Table 2b**

Pairwise comparisons from Tukey’s post-hoc tests of one-way Model I ANOVA of Tau coefficients for accuracies of mangrove mapping techniques

<table>
<thead>
<tr>
<th></th>
<th>Visual Interpretation (I)</th>
<th>Visual Interpretation (I*)</th>
<th>Unsupervised ISODATA (II)</th>
<th>Supervised SAM (III)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual Interpretation (I)</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visual Interpretation (I*)</td>
<td>0.862</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unsupervised ISODATA (II)</td>
<td>0.128</td>
<td>0.400</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Supervised SAM (III)</td>
<td>0.002**</td>
<td>0.009**</td>
<td>0.140</td>
<td>1.000</td>
</tr>
</tbody>
</table>

** = P < .01.
Table 3
Accuracy assessments for each imager and analytic technique. Analytical techniques (I–III) are defined in Table 2b. Nominal pixel sizes are given in parentheses. Accuracy means for each sensor are also shown with corresponding 95% confidence intervals (%)

<table>
<thead>
<tr>
<th>Imager</th>
<th>Technique</th>
<th>Overall Accuracy (%)</th>
<th>95% C.I. (%)</th>
<th>User's Accuracy (%)</th>
<th>95% C.I. (%)</th>
<th>Producer's Accuracy (%)</th>
<th>95% C.I. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIR PHOTO (1 m)</td>
<td>I</td>
<td>98.6</td>
<td>96.7–99.5</td>
<td>99.5</td>
<td>97.0–99.9</td>
<td>98.1</td>
<td>95.0–99.4</td>
</tr>
<tr>
<td></td>
<td>I*</td>
<td>95.5</td>
<td>92.8–97.3</td>
<td>100.0</td>
<td>97.6–100.0</td>
<td>92.3</td>
<td>87.7–95.3</td>
</tr>
<tr>
<td></td>
<td>II</td>
<td>81.5</td>
<td>77.1–85.2</td>
<td>96.1</td>
<td>91.5–98.4</td>
<td>71.0</td>
<td>64.5–76.8</td>
</tr>
<tr>
<td></td>
<td>III</td>
<td>70.3</td>
<td>65.4–74.8</td>
<td>95.5</td>
<td>89.6–98.3</td>
<td>51.2</td>
<td>44.4–57.9</td>
</tr>
<tr>
<td>AIR PHOTO (20 m)</td>
<td>I</td>
<td>98.0</td>
<td>95.9–99.1</td>
<td>99.5</td>
<td>97.7–100.0</td>
<td>96.6</td>
<td>93.1–98.5</td>
</tr>
<tr>
<td></td>
<td>I*</td>
<td>93.8</td>
<td>90.8–95.9</td>
<td>100.0</td>
<td>97.6–100.0</td>
<td>89.4</td>
<td>84.4–92.9</td>
</tr>
<tr>
<td></td>
<td>II</td>
<td>89.6</td>
<td>86.0–92.4</td>
<td>96.2</td>
<td>92.2–98.3</td>
<td>85.5</td>
<td>80.0–89.7</td>
</tr>
<tr>
<td></td>
<td>III</td>
<td>65.5</td>
<td>60.5–70.3</td>
<td>92.0</td>
<td>84.8–96.1</td>
<td>44.4</td>
<td>37.8–51.3</td>
</tr>
<tr>
<td>ASTER (30 m)</td>
<td>I</td>
<td>84.1</td>
<td>79.9–87.6</td>
<td>98.8</td>
<td>95.5–99.9</td>
<td>84.2</td>
<td>78.4–88.7</td>
</tr>
<tr>
<td></td>
<td>I*</td>
<td>90.5</td>
<td>86.9–93.2</td>
<td>98.8</td>
<td>95.5–99.9</td>
<td>84.2</td>
<td>78.4–88.7</td>
</tr>
<tr>
<td></td>
<td>II</td>
<td>86.7</td>
<td>82.7–89.9</td>
<td>96.3</td>
<td>92.0–98.5</td>
<td>79.6</td>
<td>73.4–84.7</td>
</tr>
<tr>
<td></td>
<td>III</td>
<td>70.5</td>
<td>65.5–75.1</td>
<td>99.5</td>
<td>95.3–100.0</td>
<td>48.0</td>
<td>41.1–54.9</td>
</tr>
<tr>
<td>AVTRIS (20 m)</td>
<td>I</td>
<td>89.8</td>
<td>86.2–92.6</td>
<td>98.8</td>
<td>95.6–99.9</td>
<td>83.3</td>
<td>77.5–87.8</td>
</tr>
<tr>
<td></td>
<td>I*</td>
<td>83.3</td>
<td>79.0–86.8</td>
<td>98.7</td>
<td>94.9–99.9</td>
<td>71.9</td>
<td>65.4–77.7</td>
</tr>
<tr>
<td></td>
<td>II</td>
<td>79.6</td>
<td>75.1–83.5</td>
<td>95.8</td>
<td>91.0–98.3</td>
<td>67.5</td>
<td>60.8–73.6</td>
</tr>
<tr>
<td></td>
<td>III</td>
<td>72.2</td>
<td>67.3–76.7</td>
<td>99.1</td>
<td>94.4–99.9</td>
<td>52.2</td>
<td>45.4–59.0</td>
</tr>
</tbody>
</table>
In practice, the user accuracies may be even lower than those reported because, through chance, our reference data did not include many points in the uplands that were commonly misclassified as mangroves by all three techniques.

Discussion

Optimization of Remote Sensing Tools

Previous comparisons of remote sensing tools for mangrove mapping emphasized various goals, including the importance of sensor selection for discriminating mangrove from nonmangrove vegetation (Green et al. 1998), identifying distinct mangrove assemblages in multispecies communities (Sulong et al. 2002; Wang et al. 2004), and detecting mangroves along a narrow fringe (Manson et al. 2001). In this study of a monospecific mangrove system, sensor choice had only minor impacts on the outcome of the accuracy assessments across all techniques. The result is consistent with the structure of the Rhizophora mangle zone on Molokai’s south coast: it is broad, homogeneous, and sufficiently different architecturally to allow spectral discrimination from adjacent vegetation, such as the low lying Batis maritima and shrubby Pluchea indica. Therefore, accurate results may be achieved effectively using coarser spatial resolutions (15–30 m), and decisions about the sensor of choice should focus on other characteristics, such as cost, processing time, repeatability, and management goals.

Although the high spatial resolution of aerial photography is invaluable for discriminating substrates along narrow ecotones (Manson et al. 2001), acquisitions can be expensive, particularly for large-scale coverage, and often require intensive pre- and post-processing (e.g., mosaicking, georectification) compared to other sensors. The total cost of an aerial photo survey is determined by many factors, including the age, scale, and image quality affect both the initial price and the cost of processing. Historical aerial photographs can be acquired at a low price (US$5–50 per image) but are prone to warping and require significantly more processing effort compared to the more expensive ($5,000–8,000 per flight) orthorectified aerial products currently available. The relatively small footprint of aerial photographs (usually <1 km²) also contributes to the high cost of acquisition and processing, as many images are needed to cover a relatively small research area (for example, a 10 km² region requires approximately six overlapping (60%) images at a scale of 1:20000, or 24 images at a scale of 1:5000.) In addition, this higher resolution data may add little information when mapping processes or distributions that occur at larger spatial scales: the fact that there was no significant difference in accuracy between visual interpretation of aerial photos resampled to 1 m or 20 m implies that higher spatial resolution imagery was unwarranted for mapping broad-scale R. mangle distributions. At the same time, for many coastal locations worldwide, extended archives of aerial photographs already exist and are the only source of data for assessing long-term, historical distribution changes (Dahdouh-Guebas et al. 2000; D’Iorio 2003).

Multi- and hyperspectral sensors capture a broader spectral range than aerial photographs, may be deployed at variable sampling intervals, and have advantages for rapid differentiation of mangrove assemblage types within a single community (Green et al. 1998; Rasolofoharinoro et al. 1998; Hirano et al. 2003), as long as the scale of community variation is larger than the spatial scale of one pixel. However, because all angiosperms have a similar chemical composition of chlorophylls and other organic molecules (Elvidge 1990; Kokaly et al. 1998), their spectral signatures may still remain hard to dissociate. Differences may be further obscured by environmental factors such as pollutants (e.g., defoliants, pesticides,
heavy metals), soil nutrient levels, water availability, rapid temperature flux, and abnormal concentrations of atmospheric carbon dioxide, all of which can modify spectral reflectances of plants (Woolley 1971; Filella and Penuelas 1994; Adams et al. 1999; Martini and Silver 2002; Thelen et al. 2004).

**Figure 4.** Image-derived spectral signatures from AVIRIS, ASTER and air photos for *R. mangle* growing in five different cross-shore environmental settings. Bottom right inset shows a schematic diagram of a hypothetical N-S cross section through the Pala’au mangrove habitat depicting these various environmental settings, as well as the shallow geologic structure, surface cover and morphological zonation of *R. mangle.*
When effects of environmental patchiness and/or resource availability are taken into account, intraspecific spectral variation often becomes greater than interspecific differences (Price 1994; Cochrane 2000), which can further confound classifications. Indeed, we found that mapping accuracies of both the ASTER and AVIRIS imagery were lower in the supervised SAM and unsupervised ISODATA classifications due to higher errors of omission because the algorithms failed to recognize all morphological varieties of *R. mangle*, which result from physiological responses to environmental gradients across the coastal interface (e.g., salinity, wave action, inundation, sedimentation). Dwarf mangroves, bordering the coastal interface (seaward) and the margin of the evaporate mudflat (landward), are shorter and exhibit a denser network of prop roots than the tall coastal and inland dense canopy trees (Figure 4). Protected within the rock walls of coastal fishponds, mangrove propagules and young seedlings are abundant, while larger, more mature trees buffer the interface, growing within crevices in the fishponds’ seaward facing wall. The architectural and physiological properties of dwarf mangroves on both the seaward and landward fringes produced pixels with reduced reflectance in near infrared wavelengths and increased reflectance at chlorophyll absorption wavelengths (0.45–0.52 µm and 0.63–0.69 µm), due to lower leaf densities and chlorophyll concentrations compared to trees within the tall, dense, interior canopy (Figure 4).

Many of these issues can be addressed using very high spatial resolution multi- (e.g., Quickbird, IKONOS, CASI) and hyperspectral sensors (e.g., HyMap, HyperSpecTIR). While Hirano et al. (2003) could only map a class of *R. mangle* in Florida to 40% accuracy with AVIRIS, Green et al. (1998) mapped four mangrove classes to 86% accuracy in the multispecies Turks and Caicos system, using higher spatial resolution CASI (8 bands, 1 m pixels) imagery. High spatial resolution coupled with high spectral resolution would likely reduce omission errors observed from both ASTER and AVIRIS data due to the sensors’ inability to isolate mangrove spectra from mixed pixels on the border with nonmangrove habitats, which frequently occurred in sparsely settled dwarf mangrove zones along the south shore of Molokai.

When total costs of image acquisition and labor required for processing (for both new and archival data) are balanced against classification accuracy for each sensor-analysis combination, visual interpretation and unsupervised ISODATA classifications from multispectral ASTER data produced the most favorable cost:benefit ratio for mapping mangroves on south Molokai. ASTER imagery is available in multiple formats and with varying levels of post-processing at less than $US100 per scene. Level 1B data are radiometrically and geometrically calibrated radiance at the sensor for the 14 band spectral image and require little to no post-processing aside from atmospheric and occasionally geospatial corrections. Also, unlike the aerial photographs or AVIRIS data, the entire Molokai study area was captured in one ASTER scene, requiring analysis of a single image and eliminating the processing workload associated with multiple image mosaicking and illumination adjustments. ASTER imagery is easily accessed online, provides nearly continuous global coverage, and is suitable for change detection studies with its revisit time of 16 days. Although cloud cover can be a problem and georeferencing may need to be improved with ground control, ASTER has already been used to produce robust classifications of global mangrove distributions (Haito et al. 2003). Crosstalk (when optical signals from one band leak into another band) has recently been identified as a potential problem in the SWIR region (Iwasaaki and Tonooka 2005), but free crosstalk correction software can be downloaded from the ASTER Science Project website.

Our results should not be extrapolated directly to other ecosystems; we emphasize that both the sensor and processing requirements will change based on the size of the
region of interest and the spatial and temporal scales of questions being asked (Mumby et al. 1999; Phinn et al. 2000). For instance, in multispecies mangrove systems, the advantages of high spatial resolution, hyperspectral imagery for accurately discriminating species, and species assemblages may necessitate investing in higher cost imagery. In addition, while there were no significant differences between visual classifications of Molokai mangroves by familiar and unfamiliar users, site familiarity is likely to be more important in more complex habitats. Wherever possible, data from different sources should be integrated to improve mapping resolution and accuracy (Held et al. 2003). For example, most multi- and hyperspectral data cannot be used to create stereo views in which mangrove vegetation can be classified based on height (Hirano et al. 2003), but this can be addressed by integrating the imagery with a digital elevation model (Phinn et al. 2000). Combinations of optical (e.g., photography, Landsat TM, CASI) and microwave (e.g., RADARSAT-1, synthetic aperture radar (SAR)) data can also yield higher classification accuracies than optical data alone and increase the ability to discriminate groups within mangrove assemblages (Ramsey and Jensen 1996; Souza, Filho and Paradella 2002; Held et al. 2003).

Implications for Mangroves in Hawaii

Management plans for many invasive species recommend complete removal of the nonnative species, but total eradication of Hawaiian mangroves would have complex consequences.

1. Mangrove removal might assist population recovery of the four endangered, endemic waterbirds; none of these species use mangrove habitat for foraging or nesting, and the trees provide shelter for some of their mostly nonnative predators (Adams et al. 1999).
2. Removing mangroves from areas of restricted flow, such as fishponds and anchialine pools, might improve local water quality by increasing water flow and reducing leaf litter accumulation and breakdown, which is decreasing available dissolved oxygen levels (Cox and Jokiel 1996).
3. Conversely, the sediment trapping ability of the mangroves may be improving water quality on adjacent coral reefs. On Molokai, Bigelow et al. (1989) noted reduced turbidity near high mangrove basal areas. This is consistent with data from Australia and China where mangrove forests are net sinks of terrestrially derived sediments and organic matter (Alongi and McKinnon 2005; Alongi et al. 2005).
4. Although the presence of mangroves may have increased populations of opportunistic exotics (e.g., the Samoan crab, *Scylla serrata*), it may have simultaneously increased species richness of native of soft-sediment dwellers (Demopoulos and Smith 2001).
5. In other parts of the world, mangroves also serve as important fish nursery habitats (Nagelkerken et al. 2000; Mumby et al. 2004; Islam and Wahab 2005), though specific links between mangrove area and fishery yields have yet to be determined for Hawaii.
6. Cost of complete mangrove removal would be extremely high (>\$100,000/ha with machinery, >\$350,000/ha manually; Allen 1998), and there are potentially important ecological and economic motivations for preserving certain regions.
One management practice, currently used in Hawaii, is targeted removal of mangroves from selected archaeological and important bird habitat sites. For example, mangroves were successfully controlled in the early 1990s from Kaloko and Aimakapa fishponds in the Kaloko-Honokohau National Historic Park on the main island (Pratt 1998). Both sites are culturally significant, and Aimakapa is also one of the two most important breeding sites for the Hawaiian coot and Hawaiian stilt (Pratt 1998). Mangrove control was also initiated in the mid-1990s in the Nuupia Ponds Wildlife Management Area (NPWMA) within the Kaneohe Bay Marine Corps Base on Oahu, but due to the high reproductive rate and probable lack of propagule predators, ongoing maintenance control is required (Cox and Allen 1999).

Because mangrove control is costly and not necessarily immediately effective, remote sensing tools have the potential to enable managers to prioritize sites for restoration and to monitor responses to management efforts. The rate of unmanaged mangrove encroachment into fishponds, bird habitats, or other sites of cultural significance can be quantified at a broad resolution from satellite imagery and at a finer resolution, over a longer temporal range, from aerial photography. The rates of encroachment and proximity to other mangrove patches, which may reseed cleared regions, may then be considered with site value and costs when assessing the urgency for restoration. Combining this information with thematic layers derived from remote-sensing analyses in a geographic information system can increase the power of decision making. Within a GIS, spatial statistics can then be performed to derive “hot spots” for targeted mangrove removal or those areas which should be considered for mangrove protection to enhance the ecosystem functions of sediment trapping and fisheries habitat.

Conclusion

The 1902 introduction of the red mangrove to Molokai presents a unique research opportunity to explore the applications of remote-sensing technology for monitoring invasive species in tropical coastal ecosystems. Now established on at least six of the main eight islands, the increasing distribution of *Rhizophora mangle* has encouraged review of the state’s invasive species laws and associated resource management policies, but currently the fate of *R. mangle* in Hawaii is unknown.

Remote sensing provides various options for continuous monitoring of mangrove habitat over time. Determining the most cost-effective sensor-technique combination for accurate classification of mangrove habitat is essential for building a reliable species distribution baseline that can be used for designing invasive species policy and for directing coastal resource management strategies. In the present case, unsupervised classifications from ASTER multispectral imagery were the most cost-effective options for efficiently and accurately mapping the monospecific mangrove distribution on South Molokai. However, the performance of classification techniques and from different data sources will vary depending on the complexity of the mangrove systems.

In Hawaii, monitoring the coastal change associated with mangroves is essential to understanding how the natural coastal ecosystem reacts to invasive species introductions and adapts overall to changing climatic regimes. Accurate and timely information regarding its changing distribution is critical to the management of mangrove forests throughout the Hawaiian Islands. The findings of this remote-sensing research provide a strong foundation for future mangrove monitoring, encroachment management, and integrated coastal resource planning in Hawaii.
Acknowledgements

This study was conducted as part of the Coral Reef Project of the USGS Coastal and Marine Geology (CMG) Program, and we thank all members of this research team for their support and encouragement. We also thank the NASA JPL for funding and acquiring the AVIRIS 2000 Hawaii High Altitude data. We thank Dr. Michael E. Field (USGS—CMG) for initiating and guiding this study, Dr. Gary Griggs and Dr. Eli Silver for valuable editing insights and suggestions, and Jim Maragos, Bruce Richmond, Cheryl Hapke, Ann Gibbs, Josh Logan, and Curt Storlazzi of the USGS Pacific Science Center for invaluable assistance with image processing and GIS applications. Last, we thank other members of the Hyperspectral Imaging Project (HIP) and Coastal Imaging Lab at UCSC for ongoing academic advice and scientific collaboration.

References


